Energy-Efficient Routing in Multi-Community DTN with Social Selfishness Considerations

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***Abstract*—Delay-Tolerant Networks (DTNs) are wireless mobile networks, where the nodes are sparse and end-to-end connectivity is rare. Since DTN nodes are mostly energy-limited devices, there is an immediate need to have energy-efficient routing protocols, allowing the network to perform better and function longer. Besides, in the real world, people carrying the nodes form a lot of communities because of similar interests, and they behave with social selfishness. How to improve the energy efficiency in multi-community scenarios has been an important problem. In this paper, we analytically model the performance of epidemic routing protocols in multi-community scenarios with social selfishness considerations using the Ordinary Differential Equations (ODEs). Further, an energy-efficient copy-limit-optimized algorithm based on the Box's complex method for epidemic routing is proposed, which is designed to determine the optimal copy limit in multiple communities, and can improve the energy efficiency effectively. At last, both the numerical and simulation results show that the routing protocol with the proposed algorithm can reduce the energy consumption effectively, and the impact of social selfishness is also analyzed.**

常微分方程

I. Introduction

Delay-tolerant networks (DTNs) are wireless mobile networks, where the transmission opportunities come and go from time to time, and end-to-end paths may not exist at any given time instant [1]–[3]. DTNs have been applied in many fields such as interplanetary networks, wireless sensor networks, opportunistic mobile social network, and vehicular ad hoc network, etc. [4]–[6]. Such networks often have features such as high latency and low transmission success rate. Especially, in DTNs, network nodes such as mobile phones and sensor nodes are mostly powered with battery, whose capacity is extremely limited. Thus, the energy has to be carefully planned and used in order to keep the nodes alive as long as possible in the system. Therefore, the routing protocol needs to be energy-efficient. However, one of the most typical protocols in DTNs, epidemic routing [7], does not consider this requirement and blindly forwards the messages, leading to the unwanted forwards and excessive energy consumption. Thus, a number of variants of epidemic routing to limit the message forwards are proposed [8], [9].

Furthermore, in opportunistic mobile social networks, people carrying the nodes form one or more communities with similar interests [10]. They are generally willing to spend their own resources to forward the message to those in the same community; at the same time, because of selfishness, they do not want to forward the message to those outside their community, in order to save their storage and energy. Such a social behavior is often referred to as social selfishness [11]. The impacts of social selfishness and some social-based DTN routing strategies have been studied by many researchers [11], [12].

To analyze the performance of the routing protocols, many mathematical techniques are proposed, such as Markov chain [13], [14] and Ordinary Differential Equations (ODEs) model [15]. The ODEs is a fluid variant of Markov models, under an appropriate scaling as the number of nodes increases, which has been validated as a useful tool for analyzing much more complex variants of epidemic routing [15]. However, there are few people modeling the multi-community opportunistic mobile social networks with social selfishness using ODEs and proposing a corresponding algorithm.

The main contributions of this paper are as follows:

1) A performance model of multi-community epidemic routing with social selfishness is developed with ODEs.
2) An energy-efficient copy-limit-optimized algorithm based on the Box's complex method is proposed to improve the epidemic routing protocol.
3) The energy-efficiency improvement of the routing protocol with our algorithm and the impact of social selfishness are demonstrated by numerical and simulation results.

The rest of paper is organized as follows: Section II discusses some related work in the context of DTN routing and the analytical tools used to study the performance. In Section III, we analytically model the epidemic routing with social selfishness in multiple communities using ODEs. In Section IV, an energy-efficient copy-limit-optimized algorithm based on the Box's complex method for epidemic routing is proposed. In Section V, the implementation of an epidemic routing protocol with the proposed algorithm is discussed. The performance study of the proposed algorithm is presented in Section VI. Finally, Section VII concludes the paper.

II. Related Work

Epidemic routing [7] is a typical flooding protocol in DTN, in which nodes exchange data once they meet. The flooding

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scheme disseminates copies with best effort to increase the delivery success rate and reduce the delivery delay, but more copies will consume more network resources, which are limited. So how to reduce the number of copies to improve the network performance has been a problem studied by many researchers. To this end, researchers have proposed several variants to limit the message forwards. The authors in [8] proposed Bubble Rap protocol, and used social centrality metrics among nodes to choose their forwarding strategy. The concept of immunity on the basis of the epidemic routing was proposed in [9], which prevents the copies of the message delivered successfully to disseminate continuously in the network. Besides, multi-community and social selfishness have been well-studied in sociology and economics. The authors in [12] modeled and analyzed the impact of social selfishness in epidemic routing. There are also many social-based DTN routing strategies proposed. The authors in [11] proposed a Social Selfishness Aware Routing (SSAR), handling users social selfishness in routing while maintaining an acceptable routing performance. Community-based Adaptive Spray (CAS) routing protocol is proposed in [16], which computes the shortest path from the current community to the community of the destination node and minimizes the number of copies in each community along the path with an enumeration method, while satisfying the expected delivery ratio. Bubble Rap also relies on the social characteristic (community) [8]. However, those protocols mentioned above only consider a few factors which may impact the network. In this paper, we consider comprehensively the factors of message lifetime, delivery probability, delivery delay, multi-community, and social selfishness, and propose a corresponding algorithm for epidemic routing to solve the problem.

To analyze the performance of the routing protocols, the authors in [17] used Markov model [13], [14] to analyze the impact of selfishness on the performance of epidemic algorithms. On the other hand, the authors in [15] modeled the performance of epidemic routing with ODEs. The paper shows that ODEs is a valid tool for investigating epidemic-style routing. Besides, the ODE framework can further model the recovery process. The authors in [18], [19] proposed a message-driven algorithm added to the existing routing protocols for obtaining the optimal limit of copies to improve the energy efficiency with ODEs. The authors in [20] developed an ODEs model to analyze the epidemic information dissemination in mobile social networks. However, there are few people modeling the multi-community with ODEs and proposing a corresponding algorithm.

Hence, in this paper, we model the performance of epidemic routing in multiple communities with social selfishness. Then, we analyze the combinatorial optimization problem and propose an energy-efficient copy-limit-optimized algorithm based on the Box's complex method for the copy-limited epidemic routing.

III. Performance Modeling

In our work, nodes are partitioned into non-overlapping communities. We model the social DTN as k communities denoted by $V_1, V_2, \ldots, V_k$, where V_i has N_i nodes ($i \in [1, k]$), respectively. Because nodes are sparse in DTN, they can exchange messages only when they move into the transmission range of each other. We assume that nodes move according to the Random WayPoint (RWP) mobility model, which is widely applied in the research of mobile and wireless networks as a good abstraction of realistic movement scenarios [21], and the occurrence of the contacts between any two nodes follows a Poisson process was validated in [22]. In the RWP mobility model, the inter-contact time between a pair of nodes is nearly exponentially distributed if the nodes move within a limited region and their transmission range is small compared to the region and their speed is sufficiently high [13]. Considering the heterogeneity between the inter-contact time of intra-community and inter-community, we set the average contact rate of the nodes that are inside community V_i to be λ_{ii}, and the contact rate of nodes between community V_i and V_j to be λ_{ij} ($i \neq j$). In addition, because of social selfishness, the message forwarding will be influenced, when a node encounters another node. If the two nodes are in the same community, the message is forwarded with probability p_{in}. Otherwise, the probability is p_{out}. The scenario of multi-community DTN with social selfishness is shown in Fig. 1.

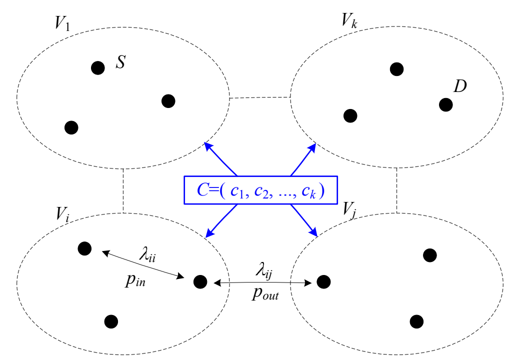

Fig. 1. Scenario of multi-community DTN with social selfishness

We now analyze the message forwarding process in k communities with social selfishness, and model it with ODEs. As shown in Fig. 1, we assume the source node S is in community V_s, which wants to send a message to the destination node D in community V_d ($s, d \in [1, k]$). Considering the energy consumption for delivering a message to the destination, we assume it is proportional to the expected number of copies forwarded during its lifetime, in which the energy consumption includes both the reception energy at the receiving node and sending energy at the transmitting node. Hence, we can show the decrease of energy consumption by enforcing the copy limit, and set the maximal number of message copies being forwarded is L. We use c_i to describe the copy limit in community V_i, which means the message at most is forwarded c_i times in community V_i, and C to represent the copy-limit vector $(c_1, c_2, \ldots, c_k)$ of all communities ($\sum_{i=1}^{k} c_i \leq L$). We let $I_i[t; C]$ represent the number of infected nodes in community V_i with the message at time t with C, $\forall i \in [1, k], I_i[t; C] \in [0, c_i]$. Correspondingly, there are $N_i - I_i[t; C]$ uninfected nodes in community V_i ($i \neq d$) and $N_d - I_d[t; C] - 1$

uninfected nodes in community V_d excluding the destination node D. When one of these uninfected nodes in V_i comes into contact with one of the infected nodes (including the source node), the number of infected nodes $I_i[t;C]$ increases if $I_i[t;C] < c_i$, otherwise $I_i[t;C]$ is not changed. The infected nodes contacting with the uninfected nodes in community V_i come from either the same community with contact rate λ_{ii} and forwarding probability p_{in} or other communities with contact rate λ_{ij} $(j \neq i)$ and forwarding probability p_{out}. The change rate of the number of infected nodes in V_i is denoted by $I_i'[t;C]$. Therefore, we can have the following equation,

$$
\begin{aligned}
I_i'[t;C] &= (N_i - I_i[t;C] - \delta_{id})(\sum_{j \neq i}^{k} I_j[t;C]\lambda_{ij}p_{\text{out}} \\
&\quad + I_i[t;C]\lambda_{ii}p_{\text{in}})
\end{aligned} \tag{1}
$$

where δ_{id} is the Kronecker delta function, i.e., δ_{id}=1 if $i = d$, and δ_{id}=0 otherwise.

In Eq. (1), $I_i'[t;C]$ is determined by the numbers of uninfected and infected nodes, as well as corresponding contact rates and forwarding probabilities. Similarly, the Cumulative probability Distribution Function (CDF) of message delivery ~~delay~~ $P[t;C]$ satisfies the following ODE,

$$
P'[t;C] = (1 - P[t;C])(\sum_{j \neq d}^{k} I_j[t;C]\lambda_{jd}p_{\text{out}} + I_d[t;C]\lambda_{dd}p_{\text{in}}) \tag{2}
$$

Eq. (2) means the message can be forwarded to the destination node D in V_d by the infected nodes from either community V_d with contact rate λ_{dd} and forwarding probability p_{in} or other communities V_j $(j \neq d)$ with λ_{jd} and p_{out}. Initially, at time $t = 0$, only the source node has the message, and the probability of the message reaching the destination node is zero. So, we let $I_s[0;C] = 1$, $I_i[0;C] = 0$ $(i \neq s)$ and $P[0;C] = 0$.

Hence, we can have the delivery ratio with the copy-limit vector C using ODEs,

$$
\text{Ratio}^C = P[E_t;C] \tag{3}
$$

where E_t is the message lifetime.

The average delivery delay with the copy-limit vector C for a message with lifetime E_t is given by [15], ?

$$
\begin{aligned}
\text{Delay}^C &= \frac{1}{P[E_t;C]} \int_0^{E_t} tP'[t;C]\mathrm{d}t \\
&= E_t - \frac{1}{P[E_t;C]} \int_0^{E_t} P[t;C]\mathrm{d}t
\end{aligned} \tag{4}
$$

When a source node wants to deliver a message to the destination node, forwards can be made by any of the relay nodes. Hence, the overall cost is the sum of the number of forwards made by nodes from different communities.

In epidemic routing, source and relay nodes both forward the message to the other node which does not have the message when they encounter. Let $F_i'[t;C]$ represent the rate of forwards made by the nodes of community V_i. Then, we can get the following equation,

$$
\begin{aligned}
F_i'[t;C] &= I_i[t;C]\Big\{ \sum_{j \neq i}^{k} (N_j - I_j[t;C])\lambda_{ij}p_{\text{out}} \\
&\quad + (N_i - I_i[t;C] - \delta_{id})\lambda_{ii}p_{\text{in}} \Big\}
\end{aligned} \tag{5}
$$

The expected number of forwards made by the nodes of community V_i at the time of reaching the destination node is the sum of the expected number of forwards before reaching the destination node and the last forward for delivering a copy of the message to the destination node made by the nodes of community V_i, which is given by,

$$
\text{Cost}_i^C = \frac{1}{P[E_t;C]} \int_0^{E_t} (F_i[t;C] + R_i[t;C])P'[t;C]\mathrm{d}t \tag{6}
$$

where

$$
R_i[t;C] = \begin{cases} \dfrac{I_i[t;C]\lambda_{id}p_{\text{out}}}{\sum_{j \neq d}^{k} I_j[t;C]\lambda_{jd}p_{\text{out}} + I_d[t;C]\lambda_{dd}p_{\text{in}}} & i \neq d \\[2ex] \dfrac{I_d[t;C]\lambda_{dd}p_{\text{in}}}{\sum_{j \neq d}^{k} I_j[t;C]\lambda_{jd}p_{\text{out}} + I_d[t;C]\lambda_{dd}p_{\text{in}}} & i = d \end{cases}
$$

Hence, we can have the total message delivery cost,

$$
\text{Cost}^C = \sum_{j=1}^{k} \text{Cost}_j^C \tag{7}
$$

IV. Energy-efficient Copy-Limit-Optimized Algorithm

According the model above, we can find that different copy-limit vector C has different message delivery cost. Since the energy consumption is proportional to the message delivery cost, optimizing the cost is equivalent to optimizing the energy. Considering the message lifetime, delivery probability, and delivery delay, we can formulate the optimization problem for the copy-limit vector C as:

$$
\begin{aligned}
&\min \quad \text{Cost}^C \\
&s.t. \begin{cases} \text{Ratio}^C & \geq \quad D_p \\ \text{Delay}^C & \leq \quad D_t \\ \sum_{j=1}^{k} c_j & \leq \quad L \end{cases}
\end{aligned} \tag{8}
$$

where D_p and D_t mean the delivery probability required and delivery delay constraint, respectively. Delay^C is the delivery delay with the copy-limit vector C.

This problem can be regarded as a classic combinatorial optimization problem. If we want to improve the energy efficiency, we should choose an appropriate copy-limit vector, with which the average delivery cost is low. Therefore, how to choose the optimal copy-limit vector is very important.

However, the number of all possible combinations of the copy-limit vector is about $\sum_{i=1}^{L}\binom{i+k-1}{k-1}$, which will increase dramatically with the increase of L and k, and makes the global optimal solution hard to be obtained by a brute-force enumeration method. Hence, we consider to use a heuristic method, i.e., the Box's complex method, to solve the problem.

Box's complex method is a widely applied direct search algorithm, which is designed for solving constrained nonlinear optimization problems and originated from the simplex method [23]. The complex is a polyhedron constituted by m points in the constraint feasible region of the n-dimensional design space. The Box's complex method is to compare the objective function value of each point of the complex, remove and replace the worst point, and gradually approach the optimal point. Since the Box's complex method does not have to differentiate and search exhaustively, it is more flexible and simpler. Besides, the process is always carried out in the feasible region, so the result is feasible as well.

For the message forwarding process in k communities with social selfishness in epidemic routing, we propose an energy-efficient copy-limit-optimized algorithm based on the Box's complex method to solve the optimization problem. The algorithm is designed to find the optimal number of copies satisfying the requirements to save the resources and increase the energy efficiency. Besides, the Box's complex method can reduce the computation time, and improve the computational efficiency. The pseudo code of the proposed algorithm is shown in Algorithm 1.

Algorithm 1 Energy-efficient copy-limit-optimized algorithm.

Input:
D_p, E_t, D_t, L, $\{N_i\}$, $\{\lambda_{ij}\}$, $p_{\text{in,out}}$, $S \in V_s$, $D \in V_d$
Output:
C^*
1: randomly generate m copy-limit vectors $C^{(i)}$, $i \in [1, m]$, $m = 2k-1$, as points to construct an initial complex and satisfy the constraints
2: $\forall i \in [1, m]$, calculate $\mathrm{Cost}^{C^{(i)}}$
3: sort $\{C^{(i)}\}$ by cost
4: $X_L \leftarrow$ the best point, $X_H \leftarrow$ the worst point, $X_G \leftarrow$ the second-worst point
5: **while** $\{\frac{1}{m}\sum_{j=1}^{k}[\mathrm{Cost}^{C^{(j)}} - \mathrm{Cost}^{X_L}]^2\}^{\frac{1}{2}} > 10^{-4}$ **do**
6: $X_C \leftarrow \frac{1}{m-1}\sum_{C^{(i)} \neq X_H} \mathrm{Cost}^{C^{(i)}}$
7: set a reflection factor α
8: **while** $\alpha > 10^{-10}$ **do**
9: $X_R \leftarrow X_C + \alpha(X_C - X_H)$
10: **if** X_R satisfies the constraints **then**
11: **if** $\mathrm{Cost}^{X_H} > \mathrm{Cost}^{X_R}$ **then**
12: $X_H \leftarrow X_R$
13: $\forall i \in [1, k]$, calculate $\mathrm{Cost}^{C^{(i)}}$
14: sort $\{C^{(i)}\}$ by cost
15: $X_L \leftarrow$ the best point, $X_H \leftarrow$ the worst point, $X_G \leftarrow$ the second-worst point
16: **break**
17: **else**
18: $\alpha \leftarrow 0.5\alpha$
19: **end if**
20: **else**
21: $\alpha \leftarrow 0.5\alpha$
22: **end if**
23: **end while**
24: **if** $\alpha < 10^{-10}$ **then**
25: $X_H \leftarrow X_G$
26: **end if**
27: **end while**
28: **return** $C^* \leftarrow X_L$

At first, m copy-limit vectors (points) are generated randomly to construct an initial complex. Each vector is in the form $C^{(i)}$ where $i \in [1, m]$, $m = 2k-1$, and satisfies the constraints in Eq. (8) (Line 1). Next, $\mathrm{Cost}^{C^{(i)}}$ is calculated at each point and the items in set $\{C^{(i)}\}$ are sorted by cost, so that, we can obtain the best point X_L, the worst point X_H and the second-worst point X_G in the set of $\{C^{(i)}\}$ (Lines 2-4). Then, the worst point X_H is replaced by a point X_R, which is α times as far from the centroid point X_C of $m-1$ points as the reflection of the worst point in the centroid. X_R, X_C and X_H are collinear (Lines 6, 7, 9 and 12). If X_R does not satisfy the constraints or is not better than X_H (Lines 10 and 11), we cut the reflection factor α by half, which makes X_R move halfway towards the centroid point X_C (Lines 18 and 21). By this way, either a feasible X_R is found or α is decreased continuously. If $\alpha < 10^{-10}$, we replace the point X_H with X_G (Lines 8 and 24-26). The procedure of replacing of the worst point is repeated until the convergence condition is met (Line 5), and then the optimal copy-limit vector C^* is obtained (Line 28).

V. Implementation Considerations

In this section, we have a discussion about the implementation of an improved epidemic routing protocol with the energy-efficient copy-limit-optimized algorithm. Assuming the all nodes know the network parameters, including $\{N_i\}$, $\{\lambda_{ij}\}$, $\forall i, j \in [1, k]$, and $p_{\text{in,out}}$, etc. When a source node wants to send a message to a destination node, it runs Algorithm 1 to obtain an optimal copy-limit vector C^* according to the destination node and the values of E_t, D_p, D_t and L. Then, the message is generated and the corresponding value of C^* is associated with it. During the routing, when an uninfected node receives a copy of the message, it computes the average number of copies having been spread to community V_i till time t using Eq. (1) in our model. Any node who finds $I_i[t; C^*] > c_i^* - 1$ will stop forwarding the message to community V_i further. That means the message will be forwarded in community V_i until the computed value c_i^* is reached. Therefore, the native epidemic routing protocol is under the control of the optimal copy-limit and its energy efficiency is improved.

VI. Performance Evaluations

In this section, we first analyze the Box's complex method applied in the proposed problem, and compare it with the enumeration method, which is used to obtain the optimal solution of the problem as a baseline. Afterwards, the performance comparisons among our protocol with the energy-efficient copy-limit-optimized algorithm and other copy-limit algorithms are shown through both numerical computation and simulation. At last, we analyze the effect of the social selfishness on the proposed algorithm.

To evaluate the Box's complex method, we assume there are 5 communities and each has 50 nodes, and set the average contact rates of intra- and inter-community are $\lambda_{ii} = 0.302$/hr and $\lambda_{ij} = 0.043$/hr, $\forall i, j \in [1, 5]$ and $i \neq j$, respectively. Besides, other parameters are set to $D_p = 0.8$, $E_t = 2,500$ s, $D_t = 2,000$ s, $L = 40$, $p_{\text{in}} = 0.8$, and $p_{\text{out}} = 0.6$.

We first analyze the calculation time of the Box's complex method affected by the reflection factor. From Fig. 2 we can find that the calculation time increases when α is smaller or larger than 1.5 for different numbers of communities. Because α determines the size of the complex, and either too small or too large complex leads to a longer convergence time of Alg. 1, we choose a value $\alpha = 1.5$ to be applied in our algorithm.

We compare the Box's complex method with the enumeration method applied in our model, in terms of the delivery cost and calculation time, with different numbers of communities. In Fig. 3, we can find that the enumeration method can obtain better results compared with the Box's complex method, and the cost of the Box's complex method has an increase of 5%. But, from Fig. 4, the calculation time increases as the number of communities increases, and more nodes will take much more calculation time under the enumeration method. Therefore, we choose the Box's complex method to be applied in our models although the result of it is a little worse.

We study our protocol via extensive simulation using the ONE simulator [24] to evaluate the theoretical model proposed in this paper. We consider a terrain size of 4,000 m $\times$ 4,000 m in which the nodes move with a velocity of 5 m/s and have a transmission range of 50 m. In the simulation, we assume the area has 4 communities and each of them has 50 nodes. Besides, we make sure that the nodes in every community move inside their community under RWP mobility model with the probability of 0.7, and outside their community with the probability of 0.3. During the simulation, we can collect the individual contact rates of any two nodes and then the average contact rates of intra- and inter-community can be obtained. We set the maximum copy $L = 40$, the delivery probability required $D_p = 0.8$, and delivery delay constraint $D_t = 2,000$ s.

To evaluate the performance, we compare the proposed protocol with other 3 protocols as follows:

1) Native protocol: an original epidemic routing without copy limitation or optimization.
2) LL protocol: an epidemic routing with L-Limited algorithm, which limits the maximum copy L, but does not optimize the cost.
3) LLO protocol: an epidemic routing with L-Limit-Optimized algorithm, which optimizes the total copies to minimize the cost similar to Algorithm 1, but does not compute the copy-limit vector on each community.

Fig. 5–7 plot the performance metrics of the proposed, native, LL and LLO protocols under the numerical computation and simulation. It can be seen that all the results of the numerical computation are consistent with those of the simulation very well, which indicates that the ODEs model we proposed in this paper is valid and able to predict the performance of the proposed protocol accurately.

Fig. 5 and 6 show the delivery cost and delivery ratio vs. message lifetime with different protocols. It is clear that the native protocol consumes the highest energy (i.e., delivery cost), and achieves the highest delivery ratio and lowest delivery delay as well, because it does not restrict the maximal number of message copies and perform any optimization based the user's requirements. In this paper, the native protocol is regarded as a baseline to show the efficiency of other improved routing protocols. The delivery cost of LL and LLO are much lower than that of the native one, but still very high compared to that of our proposed protocol. When E_t is between 2,000 and 4,000 s, our protocol maintains the delivery ratio, making it closer to the requirement through the optimal copy-limit vector C^* obtained, thereby decreasing the consumption of energy. When E_t is more than 4,000 s, the proposed protocol increases the limit of copies in C^* to satisfy the delivery delay constraint, and consequently the cost and delivery ratio are increased a little. Compared with the proposed protocol, LL protocol only limits the maximum copy and does not do any optimization on the cost. Thus, closing to L, its delivery cost is higher than other protocols, and the delivery ratio rises with an increase in the message lifetime E_t. Besides, when E_t is less than 3,000 s, LLO protocol cannot satisfy D_p under the copy limit of L, i.e., there is no feasible solution. Hence, we set the optimal solution be L, and the delivery cost and ratio are the same as those of LL protocol. After that, LLO protocol can find the optimal copy limit to reduce the delivery cost. However, it always needs larger number of copies and incurs higher cost than the proposed protocol, because LLO protocol does not compute the optimal copy-limit vector on each community. In summary, we can find that the proposed protocol can effectively improve the energy efficiency by about 50% compared to that of LLO protocol.

Fig. 7 shows the delivery delay with different protocols. With an increase of the message lifetime, the delivery delay increases. But, in our proposed protocol, since the message forwarding is controlled by fewer copies, the delivery delay will be higher than that of other protocols. In this simulation, we use $D_t = 2,000$ s to constrain delivery delay and it will achieve a good balance between the delay and the number of copies.

Then, we analyze the impacts of D_p and D_t on the performance of the proposed protocol. Fig. 8–10 show the performance metrics in terms of the delivery cost, delivery ratio and delivery delay with different D_p and D_t, respectively. From these figures, we can see that a higher D_p leads to a higher delivery cost and a lower delivery delay. Because the higher D_p needs larger limit of copies in C^* to satisfy the

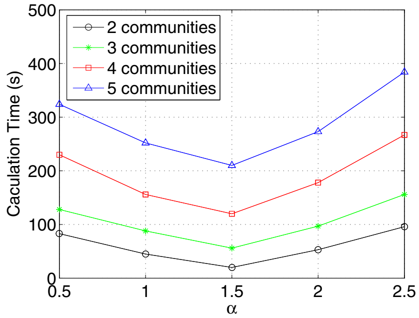

Fig. 2. Calculation time vs. reflection factor

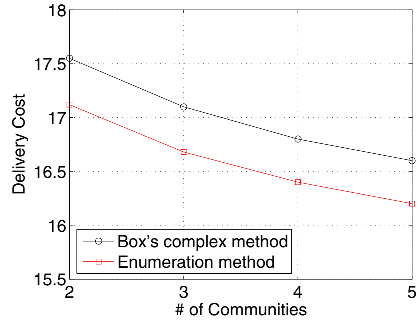

Fig. 3. Delivery cost vs. # of communities

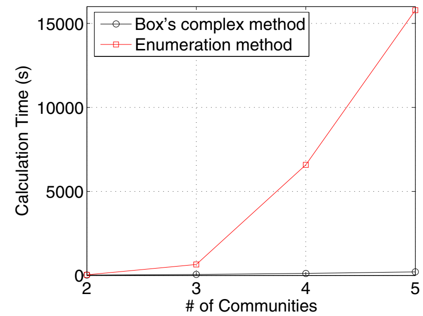

Fig. 4. Calculation time vs. # of communities

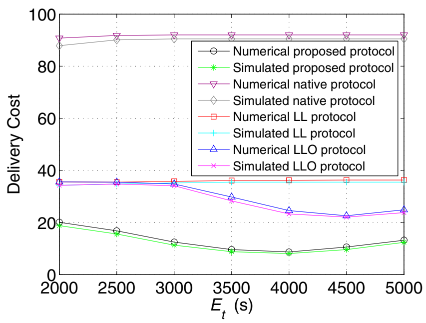

Fig. 5. Delivery cost vs. E_t with different protocols

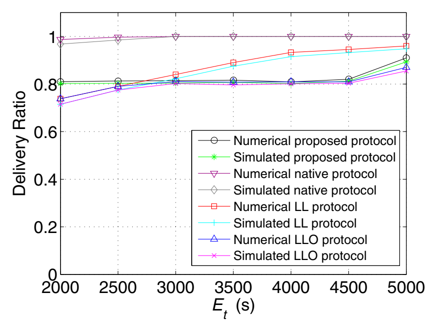

Fig. 6. Delivery ratio vs. E_t with different protocols

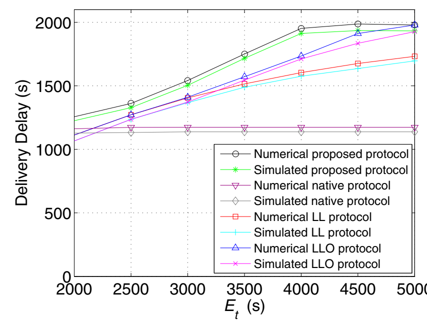

Fig. 7. Delivery delay vs. E_t with different protocols

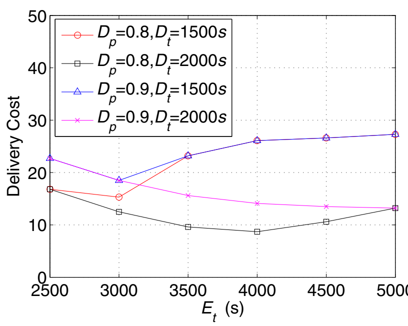

Fig. 8. Delivery cost vs. E_t with D_p and D_t

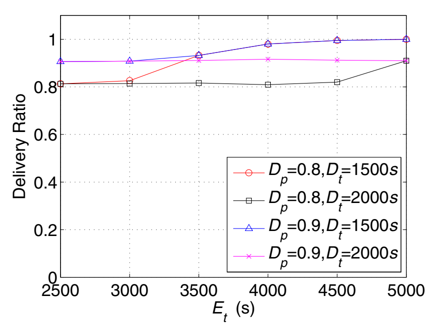

Fig. 9. Delivery ratio vs. E_t with D_p and D_t

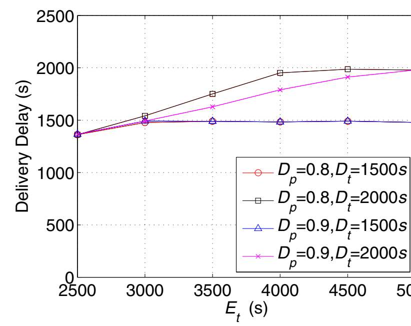

Fig. 10. Delivery delay vs. E_t with D_p and D_t

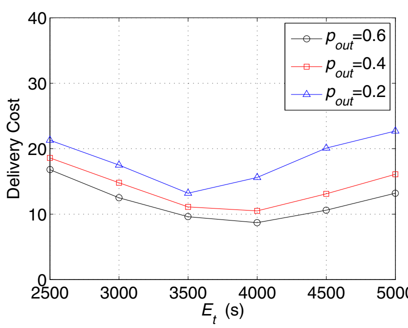

Fig. 11. Delivery cost vs. E_t with p_{out}

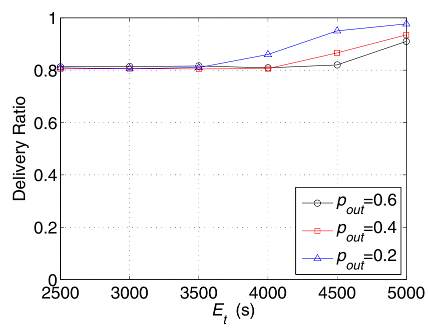

Fig. 12. Delivery ratio vs. E_t with p_{out}

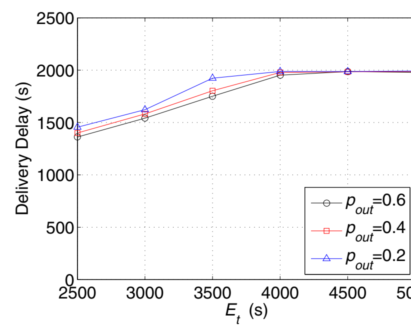

Fig. 13. Delivery delay vs. E_t with p_{out}

delivery ratio requirement. In addition, a lower D_t will also increase the delivery cost and delivery ratio, because the lower D_t needs larger limit of copies to constrain the delivery delay. Besides, In Fig. 8, when E_t is between 3,500 and 5,000 s and $D_t = 1,500$ s, the optimal cost are the same for $D_p = 0.8$ and $D_p = 0.8$ due to the delivery delay constraint.

Further, we investigate the performance metrics of the proposed protocol with different p_{out} in Fig. 11–13. Here, we set $D_p = 0.8$, $D_t = 2,000$ s and $p_{\text{in}} = 0.8$. We can find that smaller p_{out} can increase the delivery cost and delay, because a smaller p_{out} needs a larger limit of copies in C^* to increase the delivery ratio and satisfy the delivery requirement. Besides, When E_t is more than 4,000 s, because the delivery delay is constrained and smaller p_{out} has longer delivery delay, the smaller p_{out} needs to raise the number of copies in C^* much more and results in a more obvious cost increase than larger p_{out}.

VII. Conclusion

In this paper, we modeled the performance of epidemic routing in multiple communities scenarios with social selfishness using ODEs. Then, we proposed an energy-efficient copy-limit-optimized algorithm based on the Box's complex method under social DTN. By comparing the performance with other protocols, the results of both numerical calculation and simulation demonstrated the energy-efficiency improvement of the proposed protocol, while the impact of the social selfishness was also shown. In the future, we are going to study our protocol under different mobility models and extend it to multicast routing scenarios.

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